Agricultural diversification for crop yield stability: a smallholder adaptation strategy to climate variability in Ethiopia

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Abstract
Climate variability threatens food system stability, particularly among smallholders in developing countries who depend on rainfed agriculture. Farm diversification could be a relevant adaptation strategy in this context as a greater number of species or a more even distribution of crops is postulated to have a stabilizing effect on farm output as compared to a homogeneous farm. In this study, we aimed to explore relationships between climate variability, agricultural diversity, and crop yield stability. We used agriculture-focused panel data from Ethiopian households surveyed over four waves from 2011 to 2018 and two climate datasets to derive measures of long- and short-term climate variability. In a twofold analytical approach, we used mixed effects models to separately model (i) farm richness and pastoralism prevalence with climate variability as predictors, and (ii) crop yield stability with diversity, farm input, and climate characteristics as predictors. We found that farm diversity is highest in areas with high temperature variability, or low rainfall variability. This held even when excluding pastoralist households, who have naturally lower diversity. We further showed that pastoralism is least common in areas with high temperature variability and low month-to-month rainfall variability. Both crop richness and crop evenness positively affected temporal yield stability, with each showing a greater effect than irrigation, fertilizer, and pesticide usage. Together, these findings suggest that shifts in typical ranges of climate variability could destabilize farm-level crop yield for smallholders by limiting diversification opportunities. Our findings highlight the need for researchers and policymakers to consider not only the direct effects of climate variability on crop yield, but also its indirect effects on yield stability caused by increasingly limited adaptation choices.

Keywords Agricultural diversity · Yield stability · Climate variability · Ethiopia · Smallholder farmers

Introduction

Ensuring food stability under increased climate variability is a priority for food security and livelihoods, especially in lower-income and low-latitude tropical countries, which are likely to be hit hardest by the effects of climate change (Rosenzweig and Parry 1994; Rosenzweig et al. 2014; Callahan and Mankin 2022). In particular, there is medium to high confidence that climate change has already increased heat waves and droughts in sub-Saharan Africa, with detrimental impacts on agricultural productivity and

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efficiency (Otto et al. 2018; Chiang et al. 2021; Trisos et al. 2022). Increases in climate variability are responsible for both a large proportion of global yield variability in several prominent crops (Ray et al. 2015), and a reduction in national temporal yield stability as a result of destabilizing individual crop yields (Mahaut et al. 2021). Livestock is also at risk of increasing climate variability. For example, higher drought frequency can increase mortality and decrease productivity (Herrero et al. 2010; Godde et al. 2019). Smallholders are especially vulnerable to increased climate variability due to their high dependence on agriculture for their livelihoods, their strong orientation towards rainfed agricultural systems, and their often-limited capacity to cope and adapt to shocks (Ochieng et al. 2020; FAO 2021). Among the global pastoral communities, those that are currently the most socio-economically vulnerable are expected to also experience the most damaging vegetation trends for livestock production (Sloat et al. 2018; Godde et al. 2020). Such findings highlight the need among smallholders to adopt adaptation strategies that minimize crop and livestock production risks, stabilize yields, and thus improve food security.

Diversification has been suggested as a risk management strategy to adapt to climate variability and shocks. It involves increasing the variety, balance, or disparity of crops or livestock activities, which broadens the farm system's range of ecological responses to adverse conditions (Stirling 2007; Lin 2011). Both crop and livestock diversification can generally increase food security (Waha et al. 2022) although the degree to which it improves food security may be limited to a threshold (Das and Ganesh-Kumar 2018; Waha et al. 2018; Parvathi 2018). This indicates that finding the best levels for each type of diversity may be preferred over maximizing all aspects of diversity (Renard & Tilman 2019). Benefits of diversification for food security include pest and disease suppression (Lin 2011), reduced income variability and greater market opportunities (Bellon et al. 2020; Mzyece and Ng'ombe JN 2021), reduced poverty (Michler and Josephson 2017), and lower downside risk exposure for crop income (Bozzola and Smale 2020). Such benefits may not always outweigh the resources required for smallholders to implement and maintain diversification strategies, such as the financial costs, extra labor, and knowledge (Rosa-Schleich et al. 2019). However, the ability to optimize diversification based on the farmer's specific needs makes it a promising candidate for adaptation to climate variability.

While initial evidence and theory suggests a general positive effect of diversification on food security, the specific effects of diversification on temporal yield stability are still poorly understood (Beillouin et al. 2019), especially at the household level and over multiple years to decadal time scales. Literature to date offers some informative theory and observations pertaining to the effect of diversity on stability over time. For example, crop diversification at the national level stabilizes food production among many countries (Renard and Tilman 2019), including several in sub-Saharan Africa. This may be explained by the results of Mahaut et al. (2021), who found that the average yield stability of individual crops and asynchronization of yield fluctuations are both important determinants for national food production stability, and that crop diversification may improve the latter. Cereal intercropping with legumes was also found to significantly reduce the high instability of cereal yields in tropical regions (Raseduzzaman and Jensen 2017). Exploring the diversity-stability relationship at the household level with panel data can provide valuable additional insights. Indeed, as drivers of stability can depend on spatial scale (Shanafelt et al. 2015; Egli et al. 2021), household level analyses are imperative to forming valid conclusions about smallholder adaptation strategies. Moreover, the conditions faced by a household may differ significantly based on the unique combination of issues from the local scale to the global scale (Urruty et al. 2016). This heterogeneity in household responses is not considered in national-level or regional-level studies.

Here, we aim to explore the relationships between climate variability, farm diversity, and temporal yield stability with a case study in Ethiopia, using household survey panel data from rural smallholders. We accomplish this through two interrelated aims. Firstly, we aim to better understand the nature of the relationship between observed climate variability and farm diversity. Secondly, we aim to investigate any association between farm diversity and temporal yield stability. In addressing these aims, we make the following hypotheses: diversity is non-linearly associated with climate variability, such that diversity is highest at a moderate range, and lowest at the extremes of climate variability; farm livestock orientation is positively associated with climate variability; and temporal yield stability is positively associated with diversity.

Data

Household survey data

The World Bank's Living Standard's Measurement Study-Integrated Surveys on Agriculture is a collection of agriculture-focused household surveys which provide comprehensive panel data across several countries in sub-Saharan Africa. We used the Ethiopia panel dataset, which contains four waves pertaining to the primary harvest season, also called the Meher season, in 2011, 2013, 2015, and 2018 (Central Statistics Agency of Ethiopia 2011, 2013, 2015, 2018).

The analysis was disaggregated into two distinct parts corresponding to the aims of this study, and each part uses different survey waves. Firstly, we analyzed the relationship between farm diversity and climate variability using

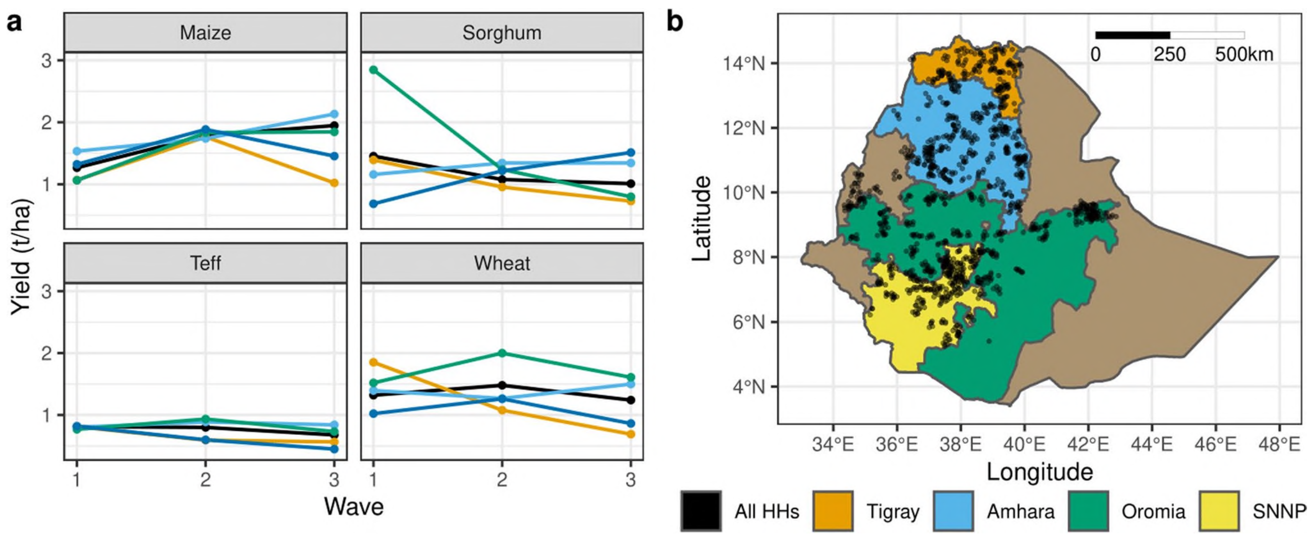

Fig. 1 Temporal yield stability in Ethiopia across three survey waves (2011 to 2015) for four selected crops (**a**) and location of surveyed households in the four most populated regions and present in all three waves 1–3 and after filtering (**b**)

cross-sectional household survey data from wave 4 in 2018. Secondly, we used household survey data from previous waves 1 to 3 to perform a longitudinal analysis investigating the effect of diversity on temporal yield stability. The latest survey wave from 2018 is a refreshed sample, and so it was not possible to link at the household level with the previous waves (CSA and World Bank 2021). Moreover, using wave 4 for the first objective rather than wave 1 to 3 ensured that the analysis was representative for all regions sampled. Indeed, the survey design for wave 1 to 3 was not intended to provide regional representativity across all regions.

We considered only rural households, and only those households that harvested crops in the most recent Meher season, or owned livestock in the past 12 months. Crop yields vary a lot from year to year and between different regions (Fig. 1a). Due to the survey design, the distribution of households within and across each region—Ethiopia's largest administrative division—is largely dependent on population density (Fig. 1b). For example, for wave 4, 1562 out of the 2521 rural households used in our analysis are from Tigray, Amhara, Oromia, or the Southern Nations, Nationalities, and Peoples' Region. The remaining households come from the other six, typically smaller, regions. Notable exceptions to this are Somali and Afar, both rather large pastoral/agro-pastoral regions, with 49 and 268 households respectively. The first three waves have a different distribution, due to the refreshed sampling for wave 4 (CSA and World Bank 2021). The World Bank's GPS anonymization process sees each household take the coordinates of its kebele—Ethiopia's smallest administrative division—which is then randomly offset by 0–5 km, with 1% of kebeles being offset by an additional 0–10 km. Each kebele's GPS coordinate is guaranteed to be within its correct zone—Ethiopia's second-largest administrative division (CSA and World Bank 2021).

For the longitudinal analysis, we filtered livestock-only households from the sample (due to data constraints) so that it only contains crop-growing and mixed crop-livestock households present for all three waves. Hence, three of the regions had very few households. The number of households per kebele was no longer ten as per the sample design, but instead averaged six households per kebele. The sample sizes for each part of the analysis, following filtering, are illustrated in Fig. 2.

Climate data

For precipitation, we used CHIRPS with daily precipitation data from 1981 to present at a 0.05 degrees resolution grid (Funk et al. 2015). We also used the Climate Research Unit's climate dataset, CRU TS v4.05, which has monthly observations from 1901 to 2020 of both precipitation and temperature at a 0.5 degrees resolution (Harris et al. 2020). This climate data was extracted at geographic locations closest to the anonymized GPS coordinates provided in the household survey data.

We calculate climate variability using the coefficient of variation (CV) of precipitation and temperature—measures commonly used to capture climate variability in agriculture. We considered two different time periods for these measures. Firstly, short-term month-to-month variability was calculated from monthly temperature and rainfall in the year prior to the survey year, to capture climate characteristics in the most recent season. Secondly, long-term annual variability

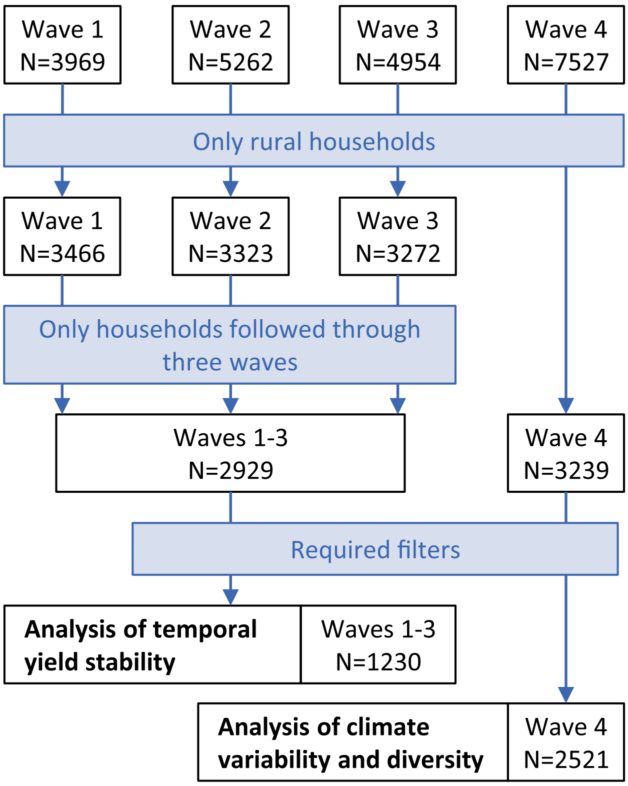

Fig. 2 Sample filtering and resulting sample size for each part of the study. It was necessary to filter households primarily to remove those that did not participate in agricultural activities, or that did not harvest any of the major 23 crops in all waves

was calculated using mean annual temperature and total annual rainfall, in the 30-year time period prior to the survey year. We initially considered additional climate variability measures but have not included in the results due to their high collinearity with 30-year climate variability. These measures were 10-year climate variability, annual variability of the long rainy season only (June–Sept), and annual variability of the short rainy season only (Feb–May).

We also calculated the Standardized Precipitation-Evapotranspiration Index (SPEI) for September in the year of each survey using the CRU dataset (Beguería et al. 2014). As the index uses both temperature and precipitation in its derivation, we used the CRU data for both the precipitation and temperature. This was calculated on a 3-month timescale—July to September. September is the last month of the long rainy season, which corresponds to the Meher season (Temam et al. 2019). From this, we derived a drought index by the number of times in the past 10 years that SPEI was less than − 1.28, following Bozzola and Smale (2020). Positive SPEI values indicate water excess and negative SPEI values indicate water deficiency. The value − 1.28 indicates severe drought events by approximately corresponding to the lower 10% tail of the SPEI probability distribution function. Based on this index, 7% of wave 4 households had no droughts, 82% had one drought, and 11% had two droughts in the long rainy season during the past 10 years. These are potentially from the major 2011/12 and 2015/16 droughts in Ethiopia (Funk et al. 2019).

Farm diversity

Diversity was captured in several ways. Species richness was defined for crops by the number of different species planted by the household in the latest cropping season, and for livestock by the number of different types owned by the household in the past 12 months. The livestock types included cattle, goat, sheep, camel, equine, chicken, and bee. Farm richness was derived as the sum of crop and livestock richness. From these richness measures, we also derived a farm specialization variable. Households with zero livestock richness were classified as crop-only, households with zero crop richness were classified as livestock-only, and the rest were classified as mixed.

Although richness measures are the simplest measures for diversity, they do not account for differences in field area usage, and thus implicitly assume equal importance of each species in a household's farming activities. We incorporated land usage using the effective diversity indices. For a household with n unique crops, let p_i be the proportion of cultivated land for crop $i \in \{1, \dots, n\}$. The Shannon diversity index provides a measure of crop evenness—the degree to which all cultivated species are equally abundant (Shannon 1948). It is given by,

$$-\sum_{i=1}^{n} p_i \ln p_i$$

The Simpson diversity index provides a measure of crop dominance—the degree to which a small subset of crop species takes up most of the cultivated area (Simpson 1949). It is given by,

$$\sum_{i=1}^{n} p_i^2$$

Finally, as a simple measure of land use diversity, we calculated the Berger-Parker diversity index, given by $1/\max(p_i)$, which is simply the inverse proportion of cultivated land of the dominant crop. Although this measure is biased towards species richness, it has the advantage of being more easily interpreted. Following Jost (2006), these three measures were transformed to get the effective diversity, which has more desirable properties compared to the raw measures. Most diversity measures for the households included in waves 1 to 3 tend to be highest in the south-west of Ethiopia (Fig. 3).

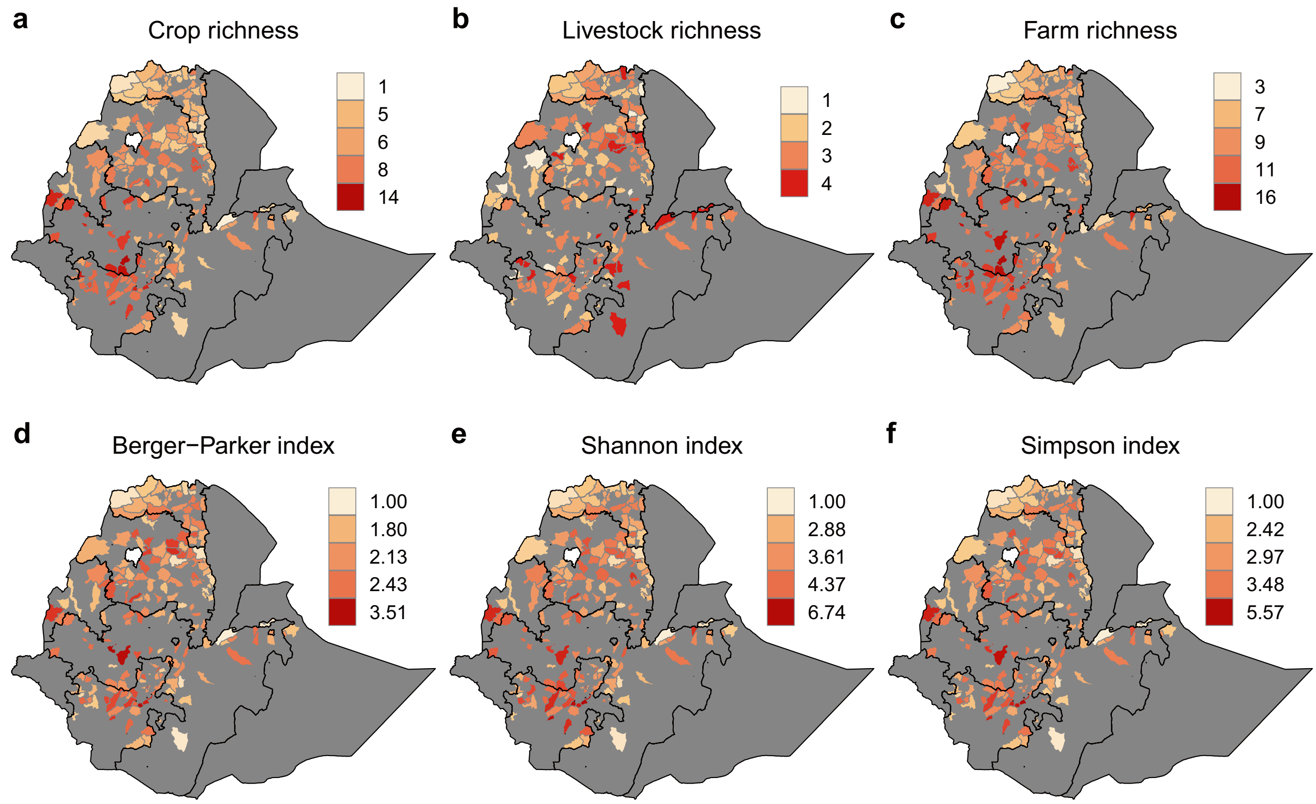

Fig. 3 Spatial distribution of effective diversity measures for the filtered households surveyed in waves 1 to 3. They are represented here as median diversity at the district level—Ethiopia's third largest administrative division after region and zone

Temporal yield stability

Caloric yield was used as a measure of average household-level crop yield. Twenty-three crops were used to derive caloric yield; these were maize, sorghum, teff, wheat, barley, millet, oats, rice, lineseed, ground nuts, nueg, rapeseed, sesame, sunflower, fenugreek, horse beans, haricot beans, field peas, chick peas, lentils, vetch, white lupin (locally called "gibto"), and soya beans. These crops were selected because they were the most comparable across waves; data collection differences made other crops unreliable for comparison across waves. To calculate a total yield across all crops, yields were converted to caloric yield using caloric content (FAO 2001) and aggregated from field to household level via an area-weighted mean. Specifically, for a given household h in wave t with crops i, the area-weighted mean caloric yield $Y_{h,t}$, is given by,

$$Y_{h,t} = \frac{\sum_i kcal_i \times harvest_i}{\sum_i area_i}$$

There is a multitude of yield stability measures defined in the literature, of which we chose six to use in our analysis. A detailed theoretical background on stability analysis is given the separately (Supplementary Information S11), which highlights why it is important to consider several alternative measures in yield stability analyses. The yield stability measure most commonly used in the literature, and thus considered in this study, is the inverse CV S_h. It is given by,

$$S_h = \frac{\mu_h}{\sigma_h} \tag{1}$$

Where μ_h is the temporal mean and σ_h is the temporal standard deviation of caloric yield of household h. Dividing by the mean gives the variability per unit of yield. Taking the inverse is merely to change interpretation from instability to stability. In addition to this measure, we implemented the alternative CV S_h, given by,

$$S_h = \sqrt{\exp\left(\sigma_h^{\star}\right) - 1}$$

where $\sigma_h^{\star}$ is the standard deviation of the log-transformed yields for each wave. This is more appropriate for variables following a log-normal distribution, as might be the case with caloric yield. To control for the effect of any yield trend over time, another two stability measures were created by detrending the CV with respect to the household's temporal trend, as well as the temporal trend of the kebele in which the household is situated. These were derived similarly to Eq. 1, but instead using a standard deviation of the residuals of a simple linear regression fit of the yield over time. We also calculated a stability measure based on power law residuals, as proposed by Döring et al. (2015), albeit in the context of the single-species yield. This measure sets a household's stability equal to its residual in the power model of yield variance on yield mean for all households, which reduces to,

$$\log\left(\sigma_{\mathrm{h}}^2\right) = \alpha \log\left(\mu_{\mathrm{h}}\right) + \beta$$

This is essentially a measure of deviation from the conditional mean yield of all households. Finally, we implemented a proportional variability index, given in our case by,

$$S_h = 1 - \frac{1}{3}\left(\frac{\min\left(Y_{h,1}, Y_{h,2}\right)}{\max\left(Y_{h,1}, Y_{h,2}\right)} + \frac{\min\left(Y_{h,2}, Y_{h,3}\right)}{\max\left(Y_{h,2}, Y_{h,3}\right)} + \frac{\min\left(Y_{h,1}, Y_{h,3}\right)}{\max\left(Y_{h,1}, Y_{h,3}\right)}\right)$$

which is a non-parametric alternative to the CV for yield stability (Heath 2006). This has the advantage of not being heavily skewed, and ranging between 0 and 1.

Statistical modeling

For each analysis, we used a mixed effects model with a random effect for kebele. Survey data tends to exhibit at least one level of clustering, based on the response variable (Rabe-Hesketh and Skrondal 2006). Ethiopian kebeles, being the smallest administrative division, are subject to similar exogenous factors. By using a mixed effects model with a kebele-level random effect, the within-kebele heterogeneity can be distinguished from the between-kebele heterogeneity, allowing us to determine whether kebeles respond in similar ways to exogenous factors such as climate variability. Although higher administrative divisions were also considered for random effects in a nested multilevel structure, the intra-class correlations were extremely low for these levels, and they were thus omitted. All models were implemented in R v4.1.3 (R Core Team 2020) using the lme4 package (Bates et al. 2015).

Climate variability and diversification

For the cross-sectional analysis, we used a generalized linear mixed effects model with a random effect for kebele (Eq. 2). Farm richness was modeled as Poisson-distributed, with precipitation and temperature variability as predictors. Temperature and precipitation are not independent predictors, but are inherently statistically associated (Table 5 in the Appendix). We do not remove one or the other from the model as they have different relevance for agriculture and differ in the magnitude and direction of effect on agriculture. In addition, an indicator variable was created to distinguish some high-leverage Somali households located in areas with extreme precipitation variability. A separate model was fitted to mixed, crop-only, and livestock-only households, as well as a model for all households pooled together. The variables used in this model are summarized in Table 3 in the Appendix.

$$\begin{aligned} \textit{Farm richness}_h \mid \varepsilon_k &\sim \mathrm{Poi}\left(e^{\beta^{\mathsf{T}} x_h + \varepsilon_k}\right) \\ \varepsilon_k &\sim \mathrm{N}\left(0, \sigma_K^2\right) \end{aligned} \tag{2}$$

To test the hypothesis that diversity is low in the extremes of climate variability, we used quadratic polynomials of climate variability as predictors. Where a variable's quadratic term has a significant and negative parameter estimate, the log-mean of farm richness is sufficiently modeled by an inverted parabola, which has a single peak. We analytically optimized those parameter estimates to determine the precise climate variability at which diversity is highest. If this peak occurs at a non-extreme climate variability, as determined by a percentile range, then diversity is lower at the extremes of climate variability in the observed data and the hypothesis is supported. A disadvantage of this methodology is that quadratics are symmetric about the peak, which may lead to under-fitting of a more complex relationship. Although other models such as splines may better capture a non-linear relationship, this would likely be limited by the availability of accurate climate data.

To determine whether the proportion of livestock-only households increases as climate variability increases, we implemented a mixed effects logistic regression model with the climate variability measures as fixed effects, and kebele as a random effect (Eq. 3). For the predictors that give significant and positive parameter estimates, the model supports the hypothesis that the proportion of livestock-only households increases as climate variability increases. The indicator for the high-leverage households used in the previous model was similarly used in this model.

$$\begin{aligned} \operatorname{logit} \mathbb{P}\left(\textit{Livestock oriented}_h\right) \mid \varepsilon_k, \varepsilon_r &= \beta^T x_h + \varepsilon_k + \varepsilon_r \\ \varepsilon_k &\sim \mathrm{N}\left(0,\ \sigma_K^2\right) \\ \varepsilon_r &\sim \mathrm{N}\left(0,\ \sigma_R^2\right) \end{aligned} \tag{3}$$

Temporal yield stability

Similar to the cross-sectional analysis, temporal yield stability was modeled using a mixed effects model with a random effect for kebele (Eq. 4). However, this model considered all available predictors as fixed effects (Table 6 in the Appendix), using variable selection procedures to reduce model size. An interaction between the diversity variable and log-transformed field area was added to examine the relationship between these variables. Exploratory analysis did not reveal large differences in slope or intercept estimates among groups, so no additional random effects were added. All numeric predictors were scaled and centered. To normalize residuals, the response variable was Box-Cox transformed, where the power parameter was calculated using the full model with kebele instead treated as a fixed effect. For robustness, we fit the same model to all six of our stability measures. The following results and discussion pertain only to the model which uses stability measured by Eq. 1—the inverse CV of caloric yield. This measure resulted in the most ideal diagnostics including normally distributed and heteroscedastic residuals. It is also the more commonly used measure in the literature, which can aid with interpretability. The results for the models using the other stability measures are reported separately (Supplementary Information S1-6).

$$\begin{aligned} Stability_h \mid \alpha_k, \varepsilon_h &= \beta^{\mathsf{T}} x_h + \alpha_k + \varepsilon_h \\ \alpha_k &\sim \mathrm{N}\left(0, \sigma_K^2\right) \\ \varepsilon_h &\sim \mathrm{N}\left(0, \sigma^2\right) \end{aligned} \tag{4}$$

Variable selection first involved developing a list of potential drivers of yield stability. We then manually inspected and eliminated variables with extreme collinearity or extreme imbalance. This was followed by backwards elimination using Akaike information criterion penalty. During backwards elimination, several variables were exempt from elimination for conditioning or for interest in the study. Namely, we retained agro-ecological zone, region, dominant crop, diversity variables, irrigation, fertilizer usage, and pesticide usage. Fertilizer usage was measured as the proportion of applied area, whereas irrigation and pesticide were measured as binary indicators of their usage on any field since the proportion of applied area for irrigation and pesticide was extremely skewed. After variable selection, 20 predictors remained in total.

The yield stability measures were derived at the household-level and encompassed all waves, whereas the predictors were often defined at lower levels and were wave-specific. This is a case of the micro–macro problem, whereby the response variable is not on the lowest level of analysis. Although predictors at the household-level and above can be handled by the usual mixed effects model framework, predictors at lower levels require further consideration. Therefore, we aggregated plot-level and field-level predictors to the household-level via area-weighted sums for continuous variables, indicators for binary variables, and most common values for categorical variables. Following this, we aggregated time-varying predictors across the three waves via the arithmetic mean for continuous variables, and most common values for binary and categorical variables. Temporal aggregation in this manner limits the ability to distinguish household heterogeneity. However, this trade-off was necessary to analyze stability, a temporal phenomenon, using only three waves. Furthermore, aggregating via simple means results in similar statistical performance to more complex methods (Foster-Johnson and Kromrey 2018).

Due to the collinearity of the diversity variables, they were used separately in three distinct models rather than combined into a single model. Collinearity of the other variables was not a problem, indicated by variance inflation factors lower than two for each variable. Farm richness, Shannon diversity, and Berger-Parker diversity were chosen for continued analysis, and the results and discussion pertain only to the three models using these variables. The variables used in the models are summarized in Table 4 in the Appendix. The results for the models using the other diversification measures are reported separately (Supplementary Information S1-6).

Results

Climate variability and diversification

We observed the following characteristics of smallholder diversity in this part of the analysis using the wave 4 household survey for 2018/2019. Livestock-only households, making up 16% of all surveyed households, are dominated primarily by goat-herders. Mixed households, which make up 74% of all households, tend to favor cattle herding, and most often have maize, teff, or sorghum as their dominant crop by area. Crop-only households, which make up the remaining 10% of all households, most often have maize, coffee, or sorghum as their dominant crop by area. This minority of households also tends to have lower crop diversity than mixed households, indicating that the tendency to specialize by way of only crop-farming is perhaps associated with the tendency to specialize within the cropping activities. Conversely, diversification by the ownership of livestock is perhaps coupled with diversification within cropping activities. Among the households that cultivate crops, 11% reported having only one crop. This behavior is more likely for crop-only households, and results in a Shannon diversity and Simpson diversity of one for those households. Farm diversity differs geographically, where the Southern Nations, Nationalities, and Peoples' Region, Amhara, and Benchsangul Gumuz were the three regions with the highest diversity. The former had an average Shannon diversity of 3.69, which is equivalent to 3.69 equally abundant crops on the average farm in this region. As expected, the two regions that are primarily livestock-only, Afar and Somali, also had the lowest diversity.

Climate variability significantly affects farm richness for both mixed and specialized (crop- or livestock-only) farm

Table 1 Results of the Poisson mixed effects model for the relationship between climate variability and farm richness

Predictors	Pooled		Mixed		Crop-only		Livestock-only	
	Log-mean (SE)	*p*-value	Log-mean (SE)	*p*-value	Log-mean (SE)	*p*-value	Log-mean (SE)	*p*-value
Intercept	1.76 (0.02)	***	1.99 (0.02)	***	1.21 (0.05)	***	0.94 (0.05)	***
Month-to-month rain CV	−4.69 (1.71)	***	−3.99 (1.25)	***	−3.83 (1.27)	***	3.48 (1.19)	***
Month-to-month rain CV^2	2.61 (1.37)	*	1.47 (1.07)		2.06 (0.99)	**	−0.80 (1.07)	
Annual rain CV	−12.43 (2.00)	***	−3.00 (1.45)	**	−2.45 (1.23)	**	−0.13 (1.30)	
Annual rain CV^2	−1.87 (1.87)		−0.55 (1.56)		−0.93 (0.88)		−1.50 (1.29)	
Month-to-month temp. CV	4.90 (1.72)	***	2.79 (1.36)	**	2.56 (1.26)	**	−2.93 (1.20)	**
Month-to-month temp. CV^2	1.86 (1.44)		0.97 (1.05)		−0.48 (0.96)		−1.67 (1.22)	
Annual temp. CV	8.90 (1.52)	***	5.70 (1.03)	***	1.83 (0.86)	**	−6.56 (1.46)	***
Annual temp. CV^2	−1.20 (1.54)		−1.82 (1.00)	*	−1.25 (0.75)	*	0.52 (1.51)	
Random effects								
σ^2	0.16		0.13		0.26		0.35	
σ^2_K	0.12		0.07		0.08		0.04	
ICC	0.42		0.34		0.24		0.10	
Marginal R^2	0.272		0.132		0.192		0.162	
Conditional R^2	0.581		0.424		0.382		0.246	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, blank = not significant

types. Specifically, results from the farm richness models (Eq. 2) indicated that climate variability predictors were statistically significant in the linear term[1] for all but the livestock-only model's annual rain variability (Table 1). For the pooled, mixed, and crop-only household models, rain variability was negatively associated with farm richness and temperature variability was positively associated with farm richness. This holds for both month-to-month and annual variability. The livestock-only model showed the opposite trends, with households in areas with higher rain variability predicted to have higher diversity, and households in lower temperature variability predicted to have higher diversity. Climate variability explained 27% of the spatial variance in farm richness among households. This was derived by pseudo-R^2 measures (Nakagawa and Schielzeth 2013). The variance explained was significantly lower for the mixed ($R^2 = 0.13$), crop-only ($R^2 = 0.19$), and livestock-only models ($R^2 = 0.16$). When also considering the kebele random effect, 58% of variance in farm richness was explained for the pooled model, with a decrease for the mixed ($R^2 = 0.42$), crop-only ($R^2 = 0.38$), and livestock-only models ($R^2 = 0.25$).

[1] As polynomial terms are only approximately orthogonal in Poisson mixed effects models, this is not necessarily indicative of the linear model with non-significant quadratic terms removed. To ensure model outcomes were similar, we refit the models with the non-significant quadratic terms removed. Statistical significance of $p < 0.05$ was maintained and signs of the estimates were the same for all but annual rain CV in the crop-only model. These results are reported separately (Supplementary Information S7-10).

In some cases, we observed non-linear relationships between climate variability and (log-)mean diversity that is indicative of a modeled peak value for farm richness. Negative quadratic parameter estimates were observed for annual temperature variability in the mixed and crop-only household models, albeit at the 0.1 significance level (Table 1). This suggests that there exists a certain annual temperature variability where diversity is highest. However, the maximum diversity predicted by the modeled polynomial was beyond the 90th percentile of the observed data, at a CV of ~ 0.027 and ~ 0.024 for the mixed and crop-only household models respectively (Fig. 4h, 1). Hence, for crop-only and mixed households, this result means that diversity is highest at high annual temperature variability, and lowest at low annual temperature variability, with no peak in the middle of the range.

The logistic regression model for livestock-only farms (Eq. 3) showed that these farms are more common in regions with high annual rainfall variability. The model also had significant parameter estimates for temperature variability (Table 2). The negative estimate for annual temperature variability implies that livestock-oriented farms become less common in climates with greater annual temperature variability. This conversely suggests that they become more common in climates with a lower mean annual temperature due to the negative correlation between temperature's variability and mean (Spearman's $\rho = -0.81, p < 0.001$) (Table 6 in the Appendix). The model also had a high intra-class correlation (ICC = 0.77) that is dominated by the variance attributable to between-kebele differences. This means that the propensity for a household to be livestock-oriented appears to be more dependent on the kebele than to the fixed effects or the region. The high intra-class

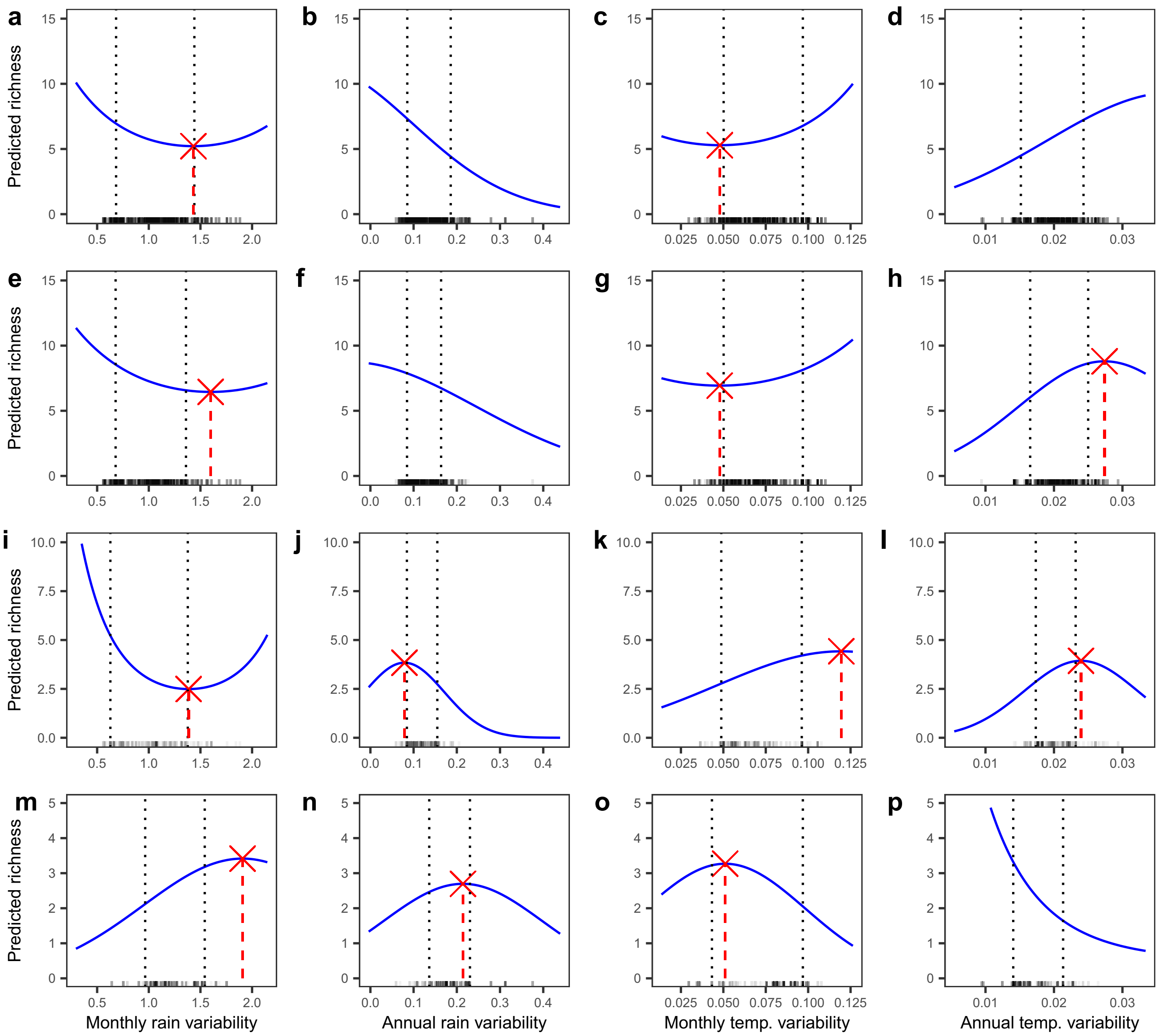

Fig. 4 Predicted farm richness (blue) for month-to-month rain variability (a, e, i, m), annual rain variability (b, f, j, n), month-to-month temperature variability (c, g, k, o), and annual temperature variability (d, h, l, p). Turning points are indicated (red) where applicable. Results are shown for the pooled households model (a, b, c, d), the mixed households model (e, f, g, h), the crop-only households model (i, j, k, l), and the livestock-only households model (m, n, o, p). Data points are plotted (black), and vertical dotted lines indicate the 10th and 90th percentiles of the observed data. Please note the different scales used for the *y*-axis

correlation is reflected in the model's conditional explained variance (conditional $R^2 = 0.87$), which is significantly lower when kebele isn't taken into account (marginal $R^2 = 0.44$).

Temporal yield stability

Temporal yield stability between 2011 and 2015 in Ethiopia had a median of 1.76. To give an example of this, a household with a stability of 1.76, or equivalently an inverse CV of $1.76^{-1} = 0.57$, could have a mean caloric yield in 1 year that was similar to its average over the three waves, with the other 2 years having a caloric mean yield 43% higher and 43% lower than the average. There are also marked regional differences in typical stability. Temporal yield stability was typically highest among households in Benshangul Gumuz and Amhara, with a median yield stability of 2.43 and 1.99 respectively. Benshangul Gumuz is a sub-humid region in the Western Ethiopian lowlands with primarily maize/sorghum mixed systems. The least stable regions were Dire Dawa and the Southern Nations, Nationalities, and Peoples' Region, with a median yield of 1.20 and 1.53 respectively. Dire Dawa is a small semi-arid region in the lowlands of Eastern Ethiopia. All households

Table 2 Results of the logistic regression mixed effects model for livestock-only farm presence

Predictors	Pooled	
	Estimate (SE)	*p*-value
Intercept	−4.92 (0.73)	***
Month-to-month rain CV	1.06 (0.59)	*
Annual rain CV	2.58 (0.66)	***
Month-to-month temp. CV	−1.23 (0.44)	***
Annual temp. CV	−1.72 (0.50)	***
Random effects		
σ^2	3.29	
σ^2_K	9.76	
σ^2_R	1.41	
ICC	0.770	
Marginal R^2	0.436	
Conditional R^2	0.872	

***$p<0.01$, **$p<0.05$, *$p<0.1$

in this region had sorghum as their dominant crop. Oromiya had the largest range of stability values, from 0.61 to 56.1, possibly due to its greater geographical extent and sample size. Furthermore, households in sub-humid climates were more stable than households in humid and semi-arid climates, where the median yield stability was 1.90 for the former, and 1.69 and 1.65 for the latter two respectively. All aforementioned descriptive results hold when considering mean, instead of median, as the measure of central tendency.

Model results for the yield stability analysis (Eq. 4) show that farm richness and Shannon diversity were significant positive predictors of stability ($p < 0.01$, Fig. 5, Table 7 in the Appendix). The estimate for Berger-Parker diversity was also positive and significant ($p < 0.01$), indicating that households which dedicate a higher proportion of crop area to the dominant crop species tend to have lower overall yield stability. This result generally held true when introducing an interaction effect between this variable and the dominant crop type. This indicates that the effect of Berger-Parker diversity is not just a function of characteristics of specific crops. Only for perennials as the dominant crop type did the effect of the Berger-Parker diversity on yield stability become negative. Crop richness and Simpson diversity gave similarly positive and significant parameter estimates to the models presented here, although livestock richness was a poor predictor for caloric yield stability both in isolation and when coupled with crop richness (Supplementary Information S1-6). Finally, the interaction between diversity and field area was not significant at the 0.05 significance level, although it was significant at the 0.1 level for the farm richness model. This model had a significant negative parameter estimate for field area, although it was smaller in magnitude than the effect of farm richness.

Parameter estimates for non-diversity predictors were mostly similar across the three models (Fig. 5, Table 7 in the Appendix). The strongest non-diversity predictor of household yield stability was the proportion of harvested area to planted area, which was statistically significant and similar

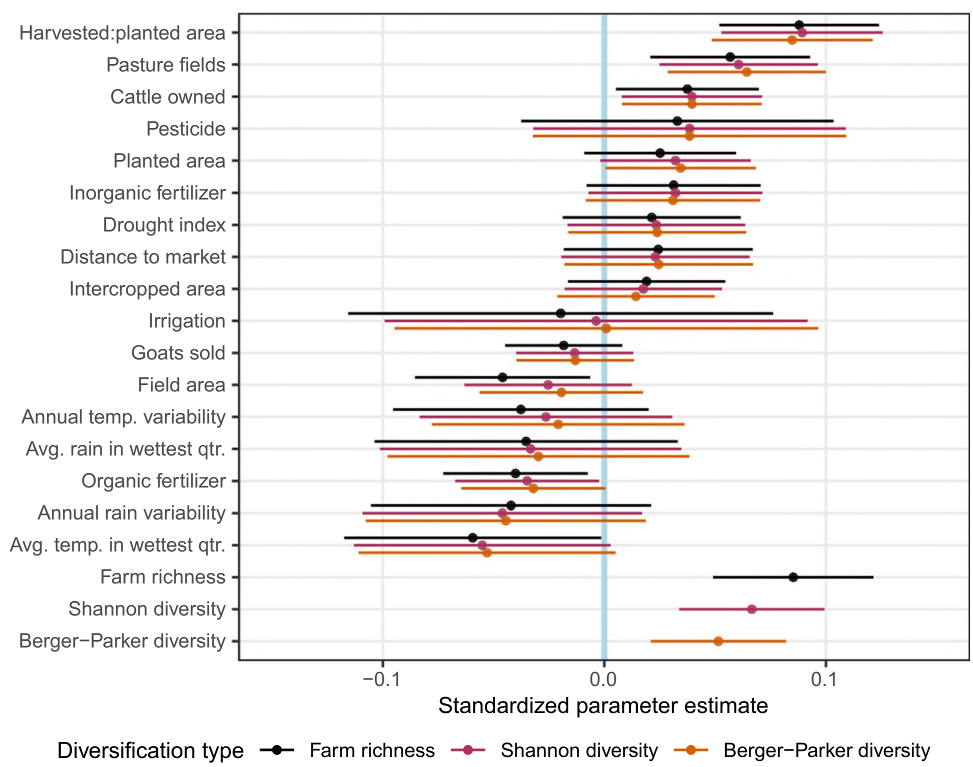

Fig. 5 Results of mixed effects model for three temporal yield stability models with different diversity measures. Dots represent parameter point estimates and lines represent 95% confidence intervals. Significant parameter estimates are those with confidence intervals that are non-overlapping with the vertical zero line

in magnitude to the effect of farm richness. The number of pasture fields was also statistically significant and positively associated with stability, as was cattle headcount albeit to a lesser extent. The proportion of area with organic fertilizer was negatively associated with stability, although not at the 0.05 significance level for one of the models. At the 0.1 level, the average temperature in the wettest quarter was the strongest negative predictor of stability. The region and dominant crop conditioning variables were significant at the 0.05 level. Intra-class correlation was low, at about 18% for all models, so stability can be quite different for households within the same kebele (Table 7 in the Appendix). The explained variance was similar for all models, with a marginal and conditional pseudo-R^2 of 0.157 and 0.315 respectively for the farm richness model. Models using the other stability measures performed similarly (Supplementary Information S1-6).

Discussion

Climate variability and diversification

We expected diversity to be low when climate variability is either very high or very low. This is because (i) highly variable climates may limit growth and development of a number of crops (Waha et al. 2018) making high crop richness less economically viable, and (ii) low variability could be more supportive of intensive monocropped farming systems (Howden et al. 2010). We find here that only climate variables taken together conform to the hypothesis. Diversity is generally lowest when precipitation variability is high and when temperature variability is low. Due to the strong negative correlation between annual temperature variability and annual mean temperature (Table 5 in the Appendix), the results also suggest that diversity is lower in warmer areas. This opposes the findings of Ochieng et al. (2020) in rural Kenyan households, which found that diversification is more widespread in warmer climates.

There are two possible explanations for this result. Firstly, the results of the logistic regression model showed that pastoralism is more prevalent in warmer areas with low annual temperature variability (Table 2). Hence, the lower diversity that is observed at the lower end of temperature variability may in fact be due to the higher frequency of livestock-oriented households, which have a low diversity overall. Secondly, the result could be explained by the characteristics of precipitation in areas with low annual temperature variability, where temperature variability is positively correlated with precipitation (Table 5 in the Appendix). Past studies show that bioclimatic variables related to precipitation were most important in Ethiopian land suitability simulations (Evangelista et al. 2013). Moreover, precipitation was often a more important factor than temperature for crop land suitability in Ghana (Chemura et al. 2020). Hence, the low diversity in areas with low temperature variability could be due to the more pervasive effects of low precipitation. Due to the limitations of observational data, any conclusions as to the causality or relative importance of either factor would need to come from external sources, such as field experiments.

An important caveat regarding interpretation of the month-to-month climate variability results is that our measure is not the average variability within all years—it is only the monthly variability that was observed in the year prior to the year of the surveys. In this context, we can consider two possible household response types to climate variability: an adaptation response to persistently high variability, and a reactionary response to recently high variability. The former is more likely captured with our measure of annual variability derived from the past 30 years. However, the latter cannot be captured with our measure of month-to-month variability in the past year. The month-to-month measure only allows us to compare recent variability between households, rather than comparing a household's recent variability to its norm. By keeping this in mind, we can put our results for this part of the study into the proper context.

Temporal yield stability

Our results show a general positive association between diversity and temporal yield stability. This aligns with theoretical and observational arguments from the literature suggesting that crop diversification can lead to more stable yields (Tilman et al. 1998; Urruty et al. 2016; Liu et al. 2019; Renard and Tilman 2019; Hufnagel et al. 2020). The effect of crop area distribution on stability is less often studied, so the observed significant positive effect of Shannon diversity is an informative outcome. Moreover, the positive effect of Berger-Parker diversity, albeit lower in magnitude than Shannon diversity, suggests that the area of the dominant crop is an important factor for yield stability, supporting the findings of Mahaut et al. (2021). As for the random effect for kebele, the models' low intraclass correlation means that households within the same kebele do not have similar stability relative to households from other kebeles. This is surprising since yield stability is very likely dependent on exogenous factors, such as weather shocks, which are essentially equal among all households within a kebele but highly varied between kebeles. It is possible that this is due to including region and agro-ecological zone as conditioning variables in the models, which might to some extent negate the effect of exogenous variables. Nevertheless, the overall effect of diversity on temporal yield stability is clear in our results, which suggests that it may be an important factor in achieving food system stability.

Several unexpected effects were observed in the yield stability model. Firstly, irrigation and inorganic fertilizer usage were not significant determinants of stability, and organic fertilizer was a negative determinant of stability. This is despite evidence that both irrigation and fertilizer use have a positive effect on both yield and yield stability (Sánchez 2010; Knapp and van der Heijden 2018; Renard and Tilman 2019; Egli et al. 2021). On the other hand, fertilizer application increases crop water requirement and in the absence of increased water supply may lead to increased crop yield variability over time (Affholder 1995; Falconnier et al. 2020). To account for potential interaction between these variables and droughts, which may affect the efficacy of irrigation and fertilizer, we also tested the model with these interaction terms included, but the results were similar. Not observing any effect in our models may be a result of diluting the variables when temporally aggregating during data preprocessing, as we had to create one variable from each time-varying variable per household from the data over all three waves. Recall bias could have also influenced the reporting on agricultural inputs (Dillon et al. 2021). Secondly, the drought index had a positive effect on stability, although it was not a significant effect. This would imply that households with a more frequent past occurrence of droughts are also more stable. One possible explanation for this is that the likelihood of droughts itself acts as a driver for adaptation measures. This is supported by findings that past climate shocks is a positive predictor of diversification in Namibian households (Mulwa and Visser 2020). As a result, there is an increased adaptive capacity among farms in areas that have experienced droughts in the past decade, and the overall stability for these households may benefit from this even during times without drought. This explanation is not examined further in this study but stands as an avenue for future work.

The role of livestock in yield stability may require a more complex approach than that taken here. Literature suggests that livestock production can be more resilient to high climate variability than crop production (Godde et al. 2021), which may also be inferred from our logistic regression model results (the "Climate variability and diversification" section). However, our models also showed that the number of livestock types owned by the household was not associated with yield stability. This could be because we did not incorporate livestock yield (e.g., meat, milk, eggs) into a single measure of overall food yield for the household. Thus, the only mechanism by which livestock diversification could increase yield stability in this model is through the indirect effects of livestock ownership, such as manure usage for soil fertility, and draught power. Furthermore, the selling of livestock to cope with shocks is an adaptation strategy which is more likely to be reflected in an income response variable than a yield response variable. Although our results did not support the implicit hypothesis that livestock diversification increases yield stability, it is quite possible that consideration of farm stability as a whole, including livestock production stability, would provide more informative outcomes.

Future research could investigate the diversity-stability relationship across the broad range of farm typologies to discover which farm types are best suited to diversification as a stability-enhancing solution. Similarly, a more crop-centric approach to stability analysis, for example looking at the yield stability of farms growing specific combinations of crops, may highlight synergistic crop species and thus help to synthesize conclusions regarding several diversification strategies simultaneously. We further note that stability as measured here did not consider macro-nutrients or micro-nutrients of crops. Given that caloric yield stability may differ from protein, carbohydrate, and fat stability in terms of the response to diversification (Egli et al. 2021), as well as the importance of micro-nutrient availability in food security for subsistence households (Sibhatu et al. 2015), follow-up studies using this aspect of crop stability are desirable. Finally, to bolster conclusions drawn in this study, we recommend continued data sharing and collection for ongoing household survey panels with a strong focus on accuracy and consistency between waves.

Barriers to implementation

Several barriers can make farm diversification difficult or infeasible for smallholders. Some of these barriers include an increasingly variable climate, climate change–driven changes in land suitability for crops (Evangelista et al. 2013; Chemura et al. 2020), lack of finance and knowledge (Ochieng et al. 2017), and a lack of investment in research, machinery, and infrastructure (Hufnagel et al. 2020). Furthermore, the benefits of diversification may not always outweigh the resources required for smallholders to implement and maintain diversification strategies, such as the financial costs, extra labor, and knowledge (Rosa-Schleich et al. 2019).

The extensive review by Lin (2011) describes several other barriers, including a lack of policy incentives, a disproportionate focus on biotech solutions, and the misconception that monocropped systems result in far greater yields. This is followed by a proposal of key strategies for overcoming these barriers, including implementation or improvement of crop and landscape simulation models, stakeholder-based participatory research, and farm income support systems (Lin 2011). In addition, access to climate information has been suggested as a strategy for opening up diversification opportunities by giving households the information needed to strategically attenuate the effects of climate change (Mulwa and Visser 2020). Our study provides more reason to invest in the aforementioned strategies to overcome barriers of implementation, thereby giving more smallholders the option to diversify and stabilize caloric yield.

When considering the role of diversification as an adaptation strategy for climate variability, it is important to weigh up any benefits with the possibility of failure under changing climatic conditions, and to do so in comparison to alternative adaptation strategies. For example, implementing or improving irrigation systems in areas with high precipitation variability is an alternative adaptation strategy which is very likely to help smallholders combat droughts and improve agricultural resilience (Temam et al. 2019). However, even if this is estimated to be a more effective long-term solution, the adoption of irrigation systems among smallholders is a multifaceted problem that could be far more difficult to overcome than the challenges of diversification (Asrat and Anteneh 2019). Moreover, although irrigation can improve stability, irrigation alone may not be enough to counteract climate variability (Mahaut et al. 2021). Therefore, the decision to diversify needs to balance the trade-off between risk reduction from climate challenges, the difficulties of choosing the right diversification strategies, and the economic constraints.

Conclusion

This study asked several questions on the relationship between farm-level diversity, climate variability, and temporal yield stability in Ethiopia and for different types of farming households. Our findings suggests that certain ranges of climate variability could destabilize household crop yield by limiting diversification opportunities.

Farm richness is lowest at high precipitation variability, which indicates higher risks for water shortage, and is maximized at high annual temperature variability in temperate climate zones. For pastoralists, the trend was opposite, and their prevalence increases with annual precipitation variability, and decreases with annual and month-to-month temperature variability.

Temporal yield stability increases with farm richness and crop evenness. This relationship supersedes the effect of other variables including farm inputs and the distance to markets. However, several variables do have a strong positive effect on stability, including the proportion of harvested to planted area and the number of pasture fields. Temporal yield stability has little dependence on locality, meaning that households in close proximity are not necessarily going to have similar yield stability.

These findings indicate that diversification opportunities for crop-growing households are highest in areas where short- and long-term rainfall variability is not excessively high, and that diversity in many forms may have a stabilizing effect on crop yields. This suggest that, for rural farming households in Ethiopia, certain ranges of climate variability could destabilize household crop yield by limiting diversification opportunities. We expect similar conclusions from other African countries with a comparable economic and climatic context to Ethiopia, but this requires further testing. There is, however, a major data challenge in assessing temporal yield stability empirically on the household level. Yield stability is vital for smallholders in developing countries, where the impact of poor crop seasons creates major threats to food security. Therefore, we suggest that researchers and policymakers consider not only the direct effects of climate change on crop yield, but also its indirect effects on yield stability caused by increasingly limited adaptation choices.

Data Availability LSMS household data is available from https://www.worldbank.org/en/programs/lsms/initiatives/lsms-ISA#11. CRU climate data is available from https://crudata.uea.ac.uk/cru/data/hrg/. CHIRPS climate data is available from https://data.chc.ucsb.edu/products/CHIRPS-2.0/. All other data is available from the authors upon reasonable request.

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